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Multi30K: Multilingual English-German Image Descriptions

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Abstract

We introduce the **Multi30K** dataset to stimulate multilingual multimodal research. Recent advances in image description have been demonstrated on English-language datasets almost exclusively, but image description should not be limited to English. This dataset extends the Flickr30K dataset with i) German translations created by professional translators over a subset of the English descriptions, and ii) German descriptions crowdsourced independently of the original English descriptions. We describe the data and outline how it can be used for multilingual image description and multimodal machine translation, but we anticipate the data will be useful for a broader range of tasks.

1 Introduction

Image description is one of the core challenges at the intersection of Natural Language Processing (NLP) and Computer Vision (CV) (Bernardi et al., 2016). This task has only received attention in a monolingual English setting, helped by the availability of English datasets, e.g. Flickr8K (Hodosh et al., 2013), Flickr30K (Young et al., 2014), and MS COCO (Chen et al., 2015). However, the possible applications of image description are useful for all languages, such as searching for images using natural language, or providing alternative-description text for visually impaired Web users.

We introduce a large-scale dataset of images paired with sentences in English and German as an initial step towards studying the value and the characteristics of multilingual-multimodal data¹.

¹The dataset is freely available under the Creative Commons Attribution NonCommercial ShareAlike 4.0 International license from <http://www.statmt.org/wmt16/multimodal-task.html>.

Multi30K is an extension of the Flickr30K dataset (Young et al., 2014) with 31,014 German *translations* of English descriptions and 155,070 independently collected German descriptions. The translations were collected from professionally contracted translators, whereas the descriptions were collected from untrained crowdworkers. The key difference between these corpora is the relationship between the sentences in different languages. In the translated corpus, we know there is a strong correspondence between the sentences in both languages. In the descriptions corpus, we only know that the sentences, regardless of the language, are supposed to describe the same image.

A dataset of images paired with sentences in multiple languages broadens the scope of multimodal NLP research. Image description with *multilingual* data can also be seen as machine translation in a *multimodal* context. This opens up new avenues for researchers in machine translation (Koehn et al., 2003; Chiang, 2005; Sutskever et al., 2014; Bahdanau et al., 2015, *inter-alia*) to work with multilingual multimodal data. Image-sentence ranking using monolingual multimodal datasets (Hodosh et al., 2013, *inter-alia*) is also a natural task for multilingual modelling.

The only existing datasets of images paired with multilingual sentences were created by professionally translating English into the target language: IAPR-TC12 with 20,000 English-German described images (Grubinger et al., 2006), and the Pascal Sentences Dataset of 1,000 Japanese-English described images (Funaki and Nakayama, 2015). **Multi30K** dataset is larger than both of these and contains both independent and translated sentences. We hope this dataset will be of broad interest across NLP and CV research and anticipate that these communities will put the data to use in a broader range of tasks than we can foresee.

1. Brick layers constructing a wall.

2. Maurer bauen eine Wand.

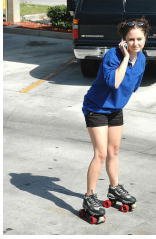


1. The two men on the scaffolding are helping to build a red brick wall.

2. Zwei Maurer mauern ein Haus zusammen.

1. Trendy girl talking on her cellphone while gliding slowly down the street

2. Ein schickes Mädchen spricht mit dem Handy während sie langsam die Straße entlangschwebt.



1. There is a young girl on her cellphone while skating.

2. Eine Frau im blauen Shirt telefoniert beim Rollschuhfahren.

(a) Translations

(b) Independent descriptions

Figure 1: Multilingual examples in the **Multi30K** dataset. The independent sentences are all accurate descriptions of the image but do not contain the same details in both languages, such as shirt colour or the scaffolding. In the second translation pair (bottom left) the translator has translated “glide” as “schweben” (“to float”) probably due to not seeing the image context (see Section 2.1 for more details).

2 The Multi30K Dataset

The Flickr30K Dataset contains 31,014 images sourced from online photo-sharing websites (Young et al., 2014). Each image is paired with five English descriptions, which were collected from Amazon Mechanical Turk². The dataset contains 145,000 training, 5,070 development, and 5,000 test descriptions. The **Multi30K** dataset extends the Flickr30K dataset with *translated* and *independent* German sentences.

2.1 Translations

The translations were collected from professional English-German translators contracted via an established Language Service in Germany. Figure 1 presents an example of the differences between the types of data. We collected one translated description per image, resulting in a total of 31,014 translations. To ensure an even distribution over description length, the English descriptions were chosen based on their relative length, with an equal number of longest, shortest, and median length source descriptions. We paid a total of €23,000 to collect the data (€0.06 per word). Translators were shown an English language sentences and asked to produce a correct and fluent translation for it in German, without seeing the image. We decided against showing the images to translators to make this process as close as possible to a standard translation task, also making the data collected here distinct from the independent

descriptions collected as described in Section 2.2.

2.2 Independent Descriptions

The descriptions were collected from crowdworkers via the Crowdfunder platform³. We collected five descriptions per image in the Flickr30K dataset, resulting in a total of 155,070 sentences. Workers were presented with a translated version of the data collection interface used by (Hodosh et al., 2013), as shown in Figure 2. We translated the interface to make the task as similar as possible to the crowdsourcing of the English sentences. The instructions were translated by one of the authors and checked by a native German Ph.D student.

185 crowdworkers took part in the task over a period of 31 days. We split the task into 1,000 randomly selected images per day to control the quality of the data and to prevent worker fatigue. Workers were required to have a German-language skill certification and be at least a Crowdfunder Level 2 Worker: they have participated in at least 10 different Crowdfunder jobs, have passed at least 100 quality-control questions, and have an job acceptance rate of at least 85%.

The descriptions were collected in batches of five images per job. Each image was randomly selected from the complete set of 1,000 images for that day, and workers were limited to writing at most 250 descriptions per day. We paid workers \$0.05 per description⁴ and prevented them from

²<http://www.mturk.com>

³<http://www.crowdfunder.com>

⁴This is the same rate as Rashtchian et al. (2010) and El-


Bildbeschreibung Auf Deutsch

Instructions ▾

Richtlinien

- Bitte beschreiben Sie die folgende fünf Bilder jeweils mit einem deutschen Satz.
- Dieser Satz soll die Aktivitäten, Menschen, Tieren und Objekte, die im Bild vorkommen, akkurat beschreiben.
- Jede Beschreibung muss ein einziger Satz mit weniger als 100 Buchstaben sein (und wahrscheinlich weniger).
- Versuchen Sie sich kurz zu fassen.
- Bitte beachten Sie korrekte Rechtschreibung und Grammatik.
- Ihre Arbeit wird akzeptiert, wenn Sie eine gute Beschreibung für alle fünf Bilder liefern und nichts leer stehen lassen.

Beispiele von guten und schlechten Beschreibungen



(1) Der Hund trägt einen roten Sombbrero.
Sehr gut: Beide Hauptobjekte werden korrekt und kurz beschrieben.

(2) Ein weißer Hund mit einem roten Hut.
Okay: Unvollständige Sätze (nur Subjekt) sind ok.

(3) Der weiße Hund trägt ein rosa Halsband.
Okay: Der Hund wird beschrieben, aber der Hut wird ignoriert.

(4) Der rote Hut ist mit goldenen Pailletten verziert.
Schlecht: Der Hund wird ignoriert.

(5) Der Hund ist schlecht gelaunt, weil er Hunger hat.
Schlecht: Spekulation anstatt Beschreibung.

(6) Ein Hund/Der Hund.
Sehr schlecht: Könnte irgendein Bild von einem Hund sein - die Beschreibung ist nicht spezifisch genug.

Figure 2: The German instructions shown to crowdworkers were translated from the original instructions.

submitting faster than 90 seconds per job to discourage poor/low-quality work. This works out at a rate of 40 jobs per hour, i.e. 200 descriptions per hour. We configured Crowdfunder to automatically ban users who worked faster than this rate. Thus the theoretical maximum wage per hour was \$10/hour. We paid a total of \$9,591.24 towards collecting the data and paying the Crowdfunder platform fees.

During the collection of the data, we assessed the quality both by manually checking a subset of the descriptions and also with automated checks. We inspected the submissions of users who wrote sentences with less than five words, and users with high type to token ratios (to detect repetition). We also used a character-level 6-gram LM to flag descriptions with high perplexity, which was very effective at catching nonsensical sentences. In general we did not have to ban or reject many users and overall description quality was high.

2.3 Translated vs. Independent Descriptions

We now analyse the differences between the translated and the description corpora. For this analysis, all sentences were stripped of punctuation and truecased using the Moses `truecaser.pl`⁵ script trained over Europarl v7 and News Commentary v11 English-German parallel corpora.

Table 1 shows the differences between the corpora. The German translations are longer than the independent descriptions (11.1 vs. 9.6 words), while the English descriptions selected for trans-

lation are slightly shorter, on average, than the Flickr30k average (11.9 vs. 12.3). When we compare the German translation dataset against an equal number of sentences from the German descriptions dataset, we find that the translations also have more word types (19.3K vs. 17.6K), and more singleton types occurring only once (11.3K vs. 10.2K; in both datasets singletons comprise 58% of the vocabulary). The translations thus have a wider vocabulary, despite being generated by a smaller number of authors. The English datasets (all descriptions vs. those selected for translation) show a similar trend, indicating that these differences may be a result of the decision to select similar numbers of short, medium, and long English sentences for translation.

2.4 English vs. German

The English image descriptions are generally longer than the German descriptions, both in terms of number of words and characters. Note that the difference is much less smaller when measuring characters: German uses 22% fewer words but only 2.5% fewer characters. However, we observe a different pattern in the translation corpora: German uses 6.6% fewer words than English but 17.1% more characters. The vocabulary of the German description and translation corpora are more than twice as large as the English corpora. Additionally, the German corpora have two-to-three times as many singletons. This is likely due to richer morphological variation in German, as well as word compounding.

liott and Keller (2013) paid to collect English sentences.

⁵<https://github.com/moses-smt/mosesdecoder/blob/master/scripts/recaser/truecaser.perl>

	Sentences	Tokens	Types	Characters	Avg. length	Singletons
Translations						
English	31,014	357,172	11,420	1,472,251	11.9	5,073
German		333,833	19,397	1,774,234	11.1	11,285
Descriptions						
English	155,070	1,841,159	22,815	7,611,033	12.3	9,230
German		1,434,998	46,138	7,418,572	9.6	26,510

Table 1: Corpus-level statistics about the translation and the description data.

3 Discussion

The **Multi30K** dataset is immediately suitable for research on a wide range of tasks, including but not limited to automatic image description, image-sentence ranking, multimodal and multilingual semantics, and machine translation. In what follows we highlight two applications in which **Multi30K** could be directly used. For more examples of approaches targeting these applications, we refer the reader to the forthcoming report on the WMT16 shared task on *Multimodal Machine Translation and Crosslingual Image Description* (Specia et al., 2016).

3.1 Multi30K for Image Description

Deep neural networks for image description typically integrate visual features into a recurrent neural network language model (Vinyals et al., 2015; Xu et al., 2015, *inter-alia*). Elliott et al. (2015) demonstrated how to build multilingual image description models that learn and transfer features between monolingual image description models. They performed a series of experiments on the IAPR-TC12 dataset (Grubinger et al., 2006) of images aligned with German translations, showing that both English and German image description could be improved by transferring features from a multimodal neural language model trained to generate descriptions in the other language. The **Multi30K** dataset will enable further research in this direction, allowing researchers to work with larger datasets with multiple references per image.

3.2 Multi30K for Machine Translation

Machine translation is typically performed using only textual data, for example news data, the Europarl corpora, or corpora harvested from the Web (CommonCrawl, Wikipedia, etc.). The **Multi30K** dataset makes it possible to further develop ma-

chine translation in a setting where multimodal data, such as images or video, are observed alongside text. The potential advantages of using multimodal information for machine translation include the ability to better deal with ambiguous source text and to avoid (untranslated) out-of-vocabulary words in the target language (Calixto et al., 2012). Hitschler and Riezler (2016) have demonstrated the potential of multimodal features in a target-side translation reranking model. Their approach is initially trained over large text-only translation corpora and then fine-tuned with a small amount of in-domain data, such as our dataset. We expect a variety of translation models can be adapted to take advantage of multimodal data as features in a translation model or as feature vectors in neural machine translation models.

4 Conclusions

We introduced **Multi30K**: a large-scale multilingual multimodal dataset for interdisciplinary machine learning research. Our dataset is an extension of the popular Flickr30K dataset with descriptions and professional translations in German.

The descriptions were collected from a crowdsourcing platform, while the translations were collected from professionally contracted translators. These differences are deliberate and part of the larger scope of studying multilingual multimodal data in different contexts. The descriptions were collected as similarly as possible to the original Flickr30K dataset by translating the instructions used by Young et al. (2014) into German. The translations were collected without showing the images to the translators to keep the process as close to a standard translation task as possible.

There are substantial differences between the translated and the description datasets. The translations contain approximately the same number of

tokens and have sentences of approximately the same length in both languages. These properties make them suited to machine translations models. The description datasets are very different in terms of average sentence lengths and the number of word types per language. This is likely to cause different engineering and scientific challenges because the descriptions are independently collected corpora instead of a sentence-level aligned corpus.

In the future, we want to study multilingual multimodality over a wider range of languages, for example beyond Indo-European families. We call on the community to engage with us on creating massively multilingual multimodal datasets.

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References

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In *ICLR*.
- Raffaella Bernardi, Ruken Cakici, Desmond Elliott, Aykut Erdem, Erkut Erdem, Nazli Ikizler-Cinbis, Frank Keller, Adrian Muscat, and Barbara Plank. 2016. Automatic description generation from images: A survey of models, datasets, and evaluation measures. *Journal of Artificial Intelligence Research*, 55:409–442.
- Iacer Calixto, Teo E. de Campos, and Lucia Specia. 2012. Images as context in statistical machine translation. In *Second Annual Meeting of the EPSRC Network on Vision & Language*.
- Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C. Lawrence Zitnick. 2015. Microsoft COCO captions: Data collection and evaluation server. *CoRR*, abs/1504.00325.
- David Chiang. 2005. A hierarchical phrase-based model for statistical machine translation. In *ACL*, pages 263–270.
- Desmond Elliott and Frank Keller. 2013. Image Description using Visual Dependency Representations. In *EMNLP*, pages 1292–1302.
- Desmond Elliott, Stella Frank, and Eva Hasler. 2015. Multi-language image description with neural sequence models. *CoRR*, abs/1510.04709.
- Ruka Funaki and Hideki Nakayama. 2015. Image-mediated learning for zero-shot cross-lingual document retrieval. In *EMNLP*, pages 585–590.
- Michael Grubinger, Paul D. Clough, Henning Muller, and Thomas Desealers. 2006. The IAPR TC-12 benchmark: A new evaluation resource for visual information systems. In *LREC*.
- Julian Hitschler and Stefan Riezler. 2016. Multimodal pivots for image caption translation. *CoRR*, abs/1601.03916.
- Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing Image Description as a Ranking Task: Data, Models and Evaluation Metrics. *Journal of Artificial Intelligence Research*, 47:853–899.
- Philipp Koehn, Franz Josef Och, and Daniel Marcu. 2003. Statistical phrase-based translation. In *NAACL*, pages 48–54.
- Cyrus Rashtchian, Peter Young, Micha Hodosh, and Julia Hockenmaier. 2010. Collecting image annotations using Amazon’s Mechanical Turk. In *NAACL-HLT Workshop on Creating Speech and Language Data with Amazon’s Mechanical Turk*.
- Lucia Specia, Stella Frank, Khalil Sima’an, and Desmond Elliott. 2016. A shared task on multimodal machine translation and crosslingual image description. In *First Conference on Machine Translation*.
- Ilya Sutskever, Oriol Vinyals, and Quoc V. V. Le. 2014. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27*, pages 3104–3112. Curran Associates, Inc.
- Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. 2015. Show and tell: A neural image caption generator. In *CVPR*.
- Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron C. Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio. 2015. Show, attend and tell: Neural image caption generation with visual attention. *CoRR*, abs/1502.03044.
- Peter Young, Alice Lai, Micha Hodosh, and Julia Hockenmaier. 2014. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*.